Ecological Indicators 103 (2019) 105–113

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Are more economic efficient solutions ignored by current policy: Cost-benefit and NPV analysis of coal-fired power plant technology schemes in China

Dan Wu[a], Xunzhou Ma[b], Shiqiu Zhang[c,*], Jiangping Ma[a]

[a] School of Environmental Science and Engineering, Sun Yat-Sen University, Guangzhou, China
[b] College of Economics, Southwest Minzu University, Sichuan, China
[c] Institute of Environment and Economy (IoEE), College of Environmental Sciences and Engineering, Peking University, Beijing, China

ARTICLE INFO

Keywords:
Cost-benefit analysis
Monte-Carlo simulation
Coal-fired power plant
Technology diversity

ABSTRACT

The broad spectrum of environmental protection technologies and their health effects have increased concern about path dependency and the "lock-in" effect. This study focuses on China's coal-fired power plants and their air pollution control technologies, due to the challenge of technology deployment in this sector. Our analysis found that there is a dominant technology scheme of air pollution control in the sector. Alternative schemes with better Net Present Value (NPV) exist beyond the dominant scheme, meaning that long-term economic efficiency is lost by implementing the current mainstream scheme. Facing the complexity and uncertainty around air pollution and climate change, this study suggests that single-technology-dominated environmental protection can pose long-term economic efficiency risks. This paper further points out the implications of technology policy improvement: paying attention to the synergy effects of air pollution technologies, the cultivation of technology diversity, the links between pollution control technology and public health objectives, and cost-benefit analysis together with NPV comparison.

1. Introduction

Path dependency can occur during technology change processes due to increasing returns from economies of scale, learning effects, network externality, and adaptive expectations (Arthur, 1989; David, 1985; Liebowitz and Margolis, 1995). Technological path dependency is usually accompanied by the "lock-in" effect, which is when a certain kind of technology dominates the market and is hard to withdraw. In the realm of energy use and climate change, the "lock-in" effect of technology is important because of the potential increase in the average global temperature as the cumulative emissions of greenhouse gases increase (Unruh, 2000, 2002; Mattauch and Edenhofer, 2015; Erickson et al., 2015).

The "lock-in" effect has not received as much attention in the area of environmental pollution as in the climate field. A major reason may be the smaller cumulative effect of environmental pollutants than greenhouse gases. However, the economic benefit or damage across the broad spectrum of environmental pollution control technology cannot be neglected (Kline, 2001).

In this paper, we discuss the economic efficiency of air pollution control technologies. Our study can be regarded as a case study of environmental pollution control technology. Air pollution currently inspires much anxiety in China due to its most important consequence: mortality risk (Chen et al., 2016). Although significant progress has been made in introducing air pollution control technologies(Feng and Liao, 2016), and $PM_{2.5}$ concentration levels may be reducing, air pollution is a long-term social issue (Song et al., 2017), in terms of China's dependency on coal, unhindered gasoline consumption, and insufficient policies on energy structure transition (Qi et al., 2016; Ho and Wang, 2014). When air pollution issues other than $PM_{2.5}$ emerge, such as O_3 pollution, which has recently appeared in some cities, we will face similar questions on accessing technology solutions and avoiding economic efficiency losses due to technology path dependency and the "lock-in" effect.

In the context of complex air pollution caused by multiple air pollutants with high concentrations reacting in the atmosphere, we focus on the coal-fired power sector in this study. This sector has an important role in emission reduction for multiple pollutants, and multiple technology options have emerged in the course of implementing air pollution control policies in China. There is ambiguity around the

* Corresponding author at: College of Environmental Sciences and Engineering, Peking University, Beijing 100871, China.
E-mail address: zhangshq@pku.edu.cn (S. Zhang).

https://doi.org/10.1016/j.ecolind.2019.02.039
Received 7 August 2018; Received in revised form 5 October 2018; Accepted 19 February 2019
Available online 06 April 2019

integrative cost efficiency of the technologies that have been utilized and not adopted, especially from a multi-pollutant control perspective. It is possible that certain technology schemes have the advantage of curbing a single targeted pollutant, but disadvantage of abating multiple pollutants. If the established technology schemes have economic efficiency losses in multi-pollutant control, policy makers should re-investigate the effectiveness of related technology policies that affect technology innovation and adoption to assess technology policies for better alleviating complex air pollution in China.

We use net present value (NPV) to screen and assess various technologies and paths. The net present value (NPV) is originally a measurement of profit calculated by subtracting the present values (PV) of cash outflows (cost, including initial cost) from the present values of cash inflows (benefit) over a period of time. NPV can be applied to public project assessment as well. A positive net present value indicates that the projected earnings generated by a project exceed the anticipated costs, meaning that the project will be a worthy one. And, the larger positive NPV is the better. NPV analysis of the technologies can give us a better understanding about whether the economic efficiencies can be further achieved.

This paper intends to answer the following questions. First, what are the major air pollution control technology schemes in the coal-fired power sector in China? Second, what kinds of technology schemes are more efficient for multiple pollutant control? Third, what is the net benefit of using more efficient technology schemes, at the plant and province levels?

The technologies used in this study include desulfurization technology (for removing sulfur dioxide (SO_2)), denitrification technology (for removing nitrogen oxide (NOx)) and dust removal technology (for removing particulate matter (PM)), as well as a pre-combustion control technology: coal washing. These technologies are both technically mature and capable of being commercialized. The desulfurization technologies used are wet limestone-gypsum flue gas desulfurization (wet FGD), the circulating fluidized bed (CFB) method and seawater (SD); the denitrification technologies used are selective non-catalytic reduction (SNCR) and selective catalytic reduction (SCR); and the dust removal technologies used are electrostatic precipitator (ESP) and bag fabric filter scrubbers (FFs).

This paper focuses on the health risks of four air pollutants emitted from coal-fired power, including SO_2, NOx, fine particulate matter ($PM_{2.5}$) and mercury (Hg). Exposure to SO_2, NOx, and some heavy metals can stimulate nose and throat, and cause bronchial constriction and expiratory dyspnea, especially for individuals with asthma (Balmes et al., 1987; Kagawa, 1984; World Health Organization, 2010). Short-term and long-term exposure to ambient particulate matter is associated with mortality and multiple diseases, including cardiovascular and cerebrovascular diseases, respiratory disease, and lung cancer (Brook et al., 2010; Ruckerl et al., 2011; Katsouyanni et al., 2001; Samet et al., 2000; Ghio and Huang, 2004; Goldberg et al., 2001; Pope III et al., 2002; Dockery et al., 1993; Pope et al., 1995; Dominici et al., 2000). Mercury in its different chemical forms also poses potential health risks and has been ranked as a hazardous pollutant that must be controlled as much as possible by the U.S. Environmental Protection Agency (EPA). It can cumulate, persist, and travel long distances in the environment (UNEP, 2013). Studies have provided evidence of mercury exposure relating to all-cause mortality and cardiovascular disease (Salonen et al., 1995; Virtanen et al., 2005). One series of studies also demonstrates the relation between mercury exposure and risk of intelligence quotient (IQ) reduction (Cohen et al., 2005; Axelrad et al., 2007; Rice et al., 2005; Crump et al., 1998).

The remainder of this paper is set out as follows. Section 2 describes the methodology of the cost and health benefit estimation, and the parameters and data for the cost-benefit analysis and Monte-Carlo simulation. Section 3 reports the estimation results. Section 4 describes our conclusions and related policy implications.

2. Methodology and data

2.1. Cost estimation

At the plant level, a typical coal-fired power plant with an installed capacity of 600 MW is assumed, to implement the technology schemes discussed in this study, which will be explained in detail in Section 2.2.1. At the provincial level, the installed capacity of the coal-fired power sector and hypothetical percentages of technology scheme implementation are assumed, to estimate the aggregate cost, which will be elaborated upon in Section 3.3.

Technology costs are estimated based on initial capital costs and annual operation and maintenance (O&M) costs. For better comparison of the costs and benefits of the technologies, the cost of one technology is indicated as an annual incremental cost per installed capacity (\$/MW·year). The annual incremental cost per MW is calculated as follows, based on data availability:

$$C_{plant} = [(C_c^{t1} * \beta_p^{t1} * \frac{(1+r)^n * r}{(1+r)^n - 1} + C_{om}^{t2})/S] * \beta_p^{t2} * \beta_r \tag{1}$$

where C_c^{t1} represents the initial capital cost (CNY) reported for year t1. C_{om}^{t2} represents the annual O&M cost (CNY/year) for year t2. β_p^{t1} and β_p^{t2} are the price indexes used to convert the prices in years t1 and t2, respectively, to the price in 1990. r is the discount rate. n is the expected lifecycle of the technology. β_r is the exchange rate of RMB to USD (USD/CNY). S represents the unit size (MW) of the plant that has implemented the corresponding technology. In this paper, data for C_c^{t1} and C_{om}^{t2} are based on the cost data reported in the related literature. For technology schemes that refer to a combination of technologies targeting different pollutants, incremental cost per installed capacity is calculated as an aggregation of the cost of the individual technology.

This study reviewed the existing Chinese literature with respect to techno-economic assessments of related technologies to screen the range of technology costs considering the varied unit sizes and coal types reported in the literature. Regarding the costs of the technologies, these Chinese literatures are focused because of the discrepancy and incommensurability of the costs between China and more developed countries. The cost parameters applied in the estimation are assumed evenly distributed and summarized in supplementary Table S.1.

2.2. Health risk valuation

Intake fractions, concentration-response coefficients, and value of a statistical life (VSL) will be used to monetize the benefits of reducing mortality and risk of respiratory diseases caused by SO_2, NOx and PM exposure. For mercury emission reduction, coefficients relating mercury emission reductions and monetized benefits based on dose response functions studies are directly applied in the estimation.

2.2.1. Definition of a standard coal-fired power plant

At the plant level, a typical coal-fired power plant with an installed capacity of 600 MW is assumed to estimate the benefit of health risk reduction. This is a typical size, because 67% of the existing plants are 600 MW size by the end of 2014 (National Bureau of Statistics of China, 2016); and new plants are required to be built with unit size being 600 MW or larger according to *Action Plan on Upgrading and Transforming Energy Conservation and Pollutants Emission Reduction in Coal-fired Power Sector (2014–2020)* (The State Council, 2014). In addition to the unit size, the typical coal-fired technology is assumed to be ultra-super critical combustion technology, which accounts for about a half of the installed capacity of coal-fired power sector (Endcoal, 2017). The base value of standard coal equivalent consumption for generating per kilowatt-hour electricity is assumed as the national average level from 2010: 312 gce/kWh (China Electricity Council, 2010). The conversion factor for raw coal and standard coal equivalent is 0.714 tce/t. The base value for running hours of a coal-fired power plant unit is assumed as

5600 h per year (National Bureau of Statistics of China, 2015a,b). The production load of the electricity generation unit is assumed as 65%. The emission factors (kg/tce) of SO_2, NOx, $PM_{2.5}$ and Hg of an uncontrolled coal-fired power plant are summarized in supplementary Table S.2.

2.2.2. Emission reduction calculation

The amount of untreated pollutants discharged from a coal-fired power plant can be calculated using the installed capacity of the plant, standard coal equivalent consumption for per-unit electricity generation, operating time per unit per year, and pollutant emission factor, as follows:

$$Q_m = S \bullet \eta \bullet T \bullet Ef_m \bullet E \tag{2}$$

where Q_m is the untreated amount of pollutant emission, S is the installed capacity of the plant, E is the standard coal equivalent consumption for per-unit electricity generation (g coal equivalent/kWh), T is the annual operating time per unit (hours), η is the unit capacity factor (%) and Ef_m is the emission factor (kg/ton coal equivalent) of the m^{th} pollutant in the absence of control technology.

The removal quantity of pollutants can be calculated using the removal rate of pollutant m, R_m, and the untreated pollutant emissions Q_m. The total pollutant removal rate of a technology scheme (technology combination) can be calculated using the removal rate of each single technology, as follows:

$$R_m = 1 - [(1-r_1)\cdot(1-r_2)\cdot\cdots\cdot(1-r_i)] \tag{3}$$

where R_m is the total removal rate of a technology scheme for pollutant *m*, and r is the removal rate of the i-th technology for pollutant *m*.

Similarly to cost parameters, removal rate data for various technologies use Chinese literature as references, because the effectiveness of technologies depends on the quality of coal used, real operation conditions, and characteristics of the power plants using the technologies. To address the integrative economic efficiency of multiple pollutant control, we review the effectiveness of technologies for removing both the targeted pollutant and other possible pollutants. The multiple pollutant removal rates of individual technologies are summarized in supplementary Table S.3

2.2.3. Intake fraction and estimation on health impact

Intake fraction is used to link pollution emission reduction and public exposure in this study, following the literature (Wang et al., 2006; Jin et al., 2017; Hammitt and Zhou, 2006; Cropper et al., 2012). Intake fraction refers to the proportion of pollutants inhaled by the recipient population during a given exposure period (Zhou et al., 2003). The intake fraction of a contaminant from a particular source can be expressed as follows:

$$iF_{j,m} = I/Q = \sum_i Popi \cdot \Delta C_{i,j} \cdot BR/q_m \tag{4}$$

where $iF_{j,m}$ is the intake fraction of pollutant j, m is pollutant j or the precursor to pollutant j, I is the pollutant amount inhaled, Q is the amount of pollutant emissions, *Popi* is the population within cell i, ΔC_{ij} is the contribution of the source to pollutant j's concentration in cell i (μg/m^3), BR is the respiration rate (20 m^3/day/person), and q_m (μg/day) is the emissions of pollutant m from the source. If the health risk is proportional to the ambient concentration of the pollution, baseline mortality and morbidity will not spatially change (Levy et al., 2009). Thus, the influence of pollutant j on healthy terminal k can be re-calculated as follows:

$$E_{j,k} = \beta_{j,k} \cdot \sum_i Popi \cdot \Delta C_{i,j} \cdot H_k \tag{5}$$

where $E_{j,k}$ (person) is population of healthy terminal k influenced by pollutant j, $\beta_{j,k}$ (%/(μg/m^3)) is the exposure-response coefficient between pollutant j and health endpoint k, H_k (%) is the mortality (or morbidity) of health endpoint k in a given year (base case). Combining formulas (4) and (5), we can calculate the health risks of the population as follows:

$$E_{j,k} = \beta_{j,k} \cdot iF_{j,k} \cdot q_m \cdot H_k/BR \tag{6}$$

The risks of all-cause death and chronic bronchitis are expressed as the endpoint of the health effect in this study. Usually, mortality can explain more than 90% of the health risks (Jin et al., 2017). The thresholds of pollutant concentration causing negative health effects are set as zero, following studies testifying that air pollution can generate adverse health effects at any concentration (World Health Organization, 2010; Pope et al., 1995; Axelrad et al., 2007).

The intake fraction data use the results of a study (Zhou et al., 2003) as a reference (see supplementary Table S.2). Intake fractions of primary particles (PM_{10}), secondary sulfate (the mass of ammonium sulfate ($(NH_4)_2SO_4$) inhaled per unit mass of SO_2 emissions), and secondary nitrate (the mass of ammonium nitrate (NH_4NO_3) inhaled per unit mass of NO_X emissions) are selected. This study (Zhou et al., 2003) estimated the intake fraction based on a 600 MW coal-fired unit located in Beijing and affecting a 3360 km^2 area, which covers most of China's densely populated regions. The distribution of most of the pollutants' inhalation factors is normal. Larger sized particles have smaller inhalation factors (Zhou et al., 2006).

2.2.4. Concentration-response coefficient selection

The selection of concentration-response (C-R) coefficients is critical for assessing health decline. In this study, C-R coefficient is parameter $\beta_{j,k}$ (%/(μg/m^3)) in formula (6). China's situation is difficult to compare with those in Europe and the United States due to various factors, including the average concentration and composition of air pollutants, the age structure of the population, and the public health system. Furthermore, existing epidemiological studies do not provide consistent methods for adjusting the C-R coefficients of developed countries to suit China's situation. Epidemiological studies usually assume that the slope of the C-R function curve is relatively steep at lower concentrations and relatively flat at higher concentrations (Burnett et al., 2014). However, some studies have emphasized that the C-R function linking the risk of $PM_{2.5}$ exposure to death may be linear across a wide range of exposure levels (Pope et al., 2014). Nevertheless, some scholars argue that no studies have shown that there is no threshold or non-linearity at higher concentrations (Zhou et al., 2006), and thus the linear or logarithmic linear form is unreasonable at high concentrations (Pope III et al., 2011; Apte et al., 2015). Hence, applying a C-R coefficient suited to Europe and the United States may misestimate the health damage caused by pollution in China.

In this study, we use the results of two studies (Cao et al., 2011; Chen et al., 2013) as references. Their results showed a long-term relationship between TSP (total suspended particulates), SO_2, and NOx exposure and mortality in China, demonstrating that an average increase of 10 μg/m^3 of the concentration of TSP, SO_2, and NO_X will increase the risk of cardiovascular mortality by 0.9%, 3.2%, and 2.3%, respectively. One study (Chen et al., 2013) used the quasi-experimental method to estimate the long-term health effects of TSP pollution in China. Their results show that an average increase of 10 μg/m^3 of the concentration of TSP will increase the risk of cardiopulmonary mortality by 2.1%. These results are comparatively lower than those of the long-term cohort study conducted in developed countries (Dockery et al., 1993; Pope et al., 1995). In this study, we use the results of one study (Cao et al., 2011) as the lower bound of the C-R coefficient, and those of the other (Chen et al., 2013) as the upper bound. The C-R parameters used for estimation are shown in supplementary Table S.2. Due to the limited C-R coefficient for mercury, a factor of economic loss from per-unit mercury emission is used.

2.2.5. Monetizing health effects

VSL is used to monetize the health effects of $PM_{2.5}$, SO_2, and NOx.

VSL is the sum of an individual's willingness to pay for a marginal mortality risk reduction (World Bank, 2007). A study (Huang et al., 2015) summarized the Chinese VSL studies, which give figures ranging from 0.15 to 0.6 million U.S. dollars calculated in 2010 prices. To match China's air pollution situation and its health effects, we set the range of VSL based on this study. With respect to the health effect endpoint of morbidity, chronic bronchitis is usually regarded as dominating the health benefits of morbidity reduction. The U.S. EPA values chronic bronchitis at 5.5% of a statistical life (U.S. EPA, 2011). This value is used in this study.

Mortality and IQ damage are usually focused on to assess the benefits of mercury abatement. In this study, coefficients relating mercury emission reduction and the monetized benefits of IQ damage aversion based on dose response function studies (Shih and Tseng, 2015; Spadaro and Rabl, 2008) are applied, to estimate the benefit of avoiding population IQ loss from mercury exposure. The values found by two studies (Spadaro and Rabl, 2008; Shih and Tseng, 2015) are set as the lower and upper bounds, respectively. The benefit of avoiding death from mercury exposure is then estimated based on studies comparing the benefits of avoiding IQ damage and death. According to these two studies (Sundseth et al., 2010; Shih and Tseng, 2015), the welfare gained from avoiding death from methyl mercury exposure is 4.7 times that of avoiding IQ damage. However, in another study (Sundseth et al., 2010), which covers the globe, the welfare gained from avoiding death from methyl mercury exposure is more than 7 times that of avoiding IQ damage. Thus, a sevenfold factor is used in our calculation.

At the plant level, the annual health benefit of death avoidance from $PM_{2.5}$, SO_2, NOx, and Hg emissions from a technology scheme can be calculated by the following formulas, which are developed based on formula (6), respectively:

$$B_{pm2.5} = (Q_m * R_m * IFp_{PM2.5} * CR_{mort} * incidence_{mort}/(BR * 365) * VSL) / S * \beta_p^{t3} \quad (7)$$

$$B_{SO2} = (Q_m * R_m * IFp_{SO2} * CR_{mort} * incidence_{mort}/(BR * 365) * VSL) / S * \beta_p^{t3} \quad (8)$$

$$B_{NOx} = (Q_m * R_m * IFp_{NOx} * CR_{mort} * incidence_{mort}/(BR * 365) * VSL) / S * \beta_p^{t3} \quad (9)$$

$$B_{Hg} = (Q_m * R_m * b_{Hg})/S * \beta_p^{t3} \quad (10)$$

where $B_{pm2.5}$($/MW), B_{SO2}($/MW), B_{NOx} ($/MW), and B_{Hg}($/MW) is benefit from curbing PM2.5, SO2, NOx and mercury per MW, respectively, Q_m (g) is uncontrolled annual $PM_{2.5}$ emissions from the assumed coal-fired power plant, R_m (%) is the total removal rate of $PM_{2.5}$ from the mth technology scheme, $IFp_{PM2.5}$, IFp_{SO2}, and IFp_{NOx} represent the intake fractions of primary $PM_{2.5}$, SO_2, and NOx emissions, respectively, from the assumed plant, CR_{mort} (%/(μg/m^3)) represents the concentration-response coefficient of chronic mortality, $incidence_{mort}$ (%) represents all-cause mortality, BR is the respiration rate (20 m^3/day/person), 365 is annual days, VSL represents the value of a statistical life ($), S (MW) is the installed capacity of the plant, b_{Hg} represents the benefit from abating per gram of mercury emissions ($/g), and β_p^{t3} is the price index used to convert the price in benefit calculation year t3 to the price in 1990.

2.3. Cost-benefit analysis and Monte-Carlo simulation

A cost-benefit analysis is conducted to determine the economic efficiency of the technology schemes. The net present value (NPV) of the mth technology scheme is calculated as follows:

$$NPV_m = (B_{pm2.5,m} + B_{SO2,m} + B_{NOx,m} + B_{Hg,m}) - C_{plant,m}$$

where NPV_m, $B_{pm2.5,m}$, $B_{SO2,m}$, $B_{NOx,m}$, $B_{Hg,m}$, and $C_{plant,m}$ refer to net present value, annual health benefit from abating $PM_{2.5}$, SO_2, NOx, and Hg per MW, and annual incremental cost per MW of the mth technology scheme, respectively.

The previous formulas show that multiple uncertain parameters must be input to estimate the NPV of technology schemes. Here, Monte-Carlo simulations are used to simulate the NPV probability of various technology schemes at the plant level, and the net benefit of technology scheme substitution at the provincial level. The baseline and the upper and lower bounds of simulation parameters are listed in supplementary Table S.2. It is assumed that the all of the parameters are evenly distributed in the model, following a similar study (Jin et al., 2017). The correlation between the initial capital cost (of wet FGD, CFB, SD, SCR, ESP, and FFs) and expected lifecycle is assumed to be 0.5 in the simulation (Jin et al., 2017).

2.4. Scenario analysis

At the sector level, we examine the national desulfurization and denitration facility inventory from 2014 as disclosed by China's Ministry of Environmental Protection (MEP) (MEP of China, 2014), to estimate the proportions of various technology schemes. Then, to estimate the technology cost at the provincial level, we assume the installed capacity of the coal-fired power sector and the hypothetical percentages of implementing various technology schemes, according to related government plans. Finally, we estimate the provincial NPV of technology scheme substitution.

3. Results and discussion

3.1. Air pollution control technology schemes

The national desulfurization and denitration facility inventory (2014) notes 4467 coal-fired power units installed with desulfurization facilities and 1135 coal-fired power units installed with denitration facilities. According to the total installed capacity of the coal-fired power sector in 2013, the listed desulfurization units accounted for 94.6% of the total. In terms of statistics, the proportion of installed capacity of wet FGD technology to the total installed capacity of desulfurization units increased from 34.1% to 82.3% of between 2004 and 2013. The occupation of SCR in the denitration technology market had been more than 90.0% since early 2000s and reached 95.3% in 2013. Meanwhile, ESP accounted for about 80% of the total installed capacity of the sector (Liu, 2014).

The markets for desulfurization, denitration, and de-dusting demonstrate that there is a major technology scheme (i.e., a combination of technologies targeting different pollutants) in the coal-fired power sector: "wet FGD + SCR + ESP," which occupied an estimated 57.4% of the sector's total capacity in 2013. Other potential alternatives not widely deployed in the market exist: "CFB + SCR + ESP," "SD + SCR + ESP," "CFB + SCR + FFs," "SD + SCR + FFs," "coal washing + CFB + SCR + FFs," and "coal washing + SD + SCR + FFs." Although these schemes do not remove the targeted pollutants as efficiently as the mainstream scheme, they may have better performance in removing non-targeted pollutants.

3.2. NPV of each technology scheme at the plant level

The cumulative probability distribution of the NPV of the mainstream technology scheme used in a typical coal-fired power plant located in Beijing is estimated based on the methodology developed in Section 2. The same estimation is applied to alternative schemes. The results show that the base NPV of the mainstream technology scheme (wet FGD + SCR + ESP), which is estimated using the median value of the parameters, is about 93.5 million U.S. dollars (see Fig. 1). The probability of the net benefit being greater than 93.5 million U.S. dollars is about 52.48%. The other potential alternatives,

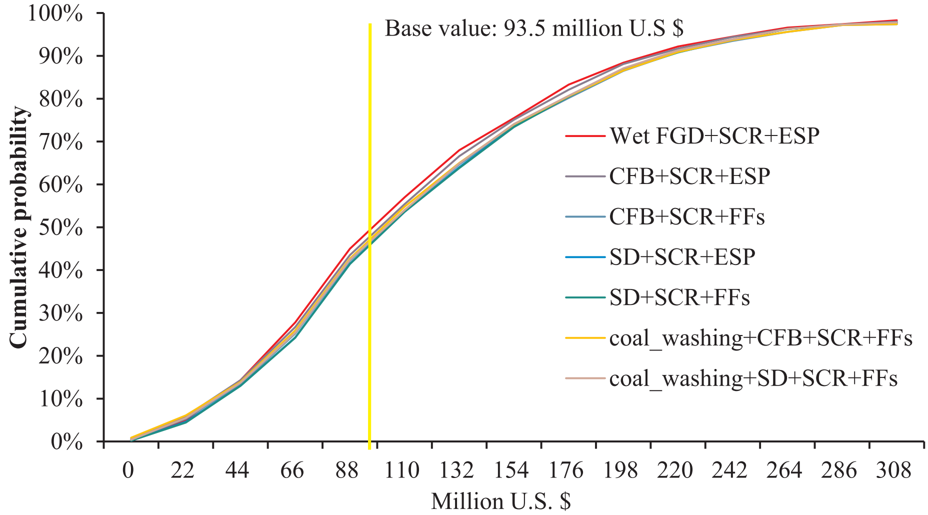

Fig. 1. Cumulative probability distribution of the NPV of various technology schemes at plant level.

"CFB + SCR + ESP," "SD + SCR + FFS," "CFB + SCR + FFs," "SD + SCR + ESP," "coal washing + SD + SCR + FFs," and "coal washing + CFB + SCR + FFs," have higher probabilities of being greater than 93.5 million U.S. dollars at 54.44%, 57.60%, 56.03%, 57.31%, 56.60% and 55.65%, respectively. In the range of 0 to 330 million U.S. dollars in which the cumulative probabilities vary from 0% to 100%, the cumulative probability of the NPV of the mainstream scheme (wet FGD + SCR + ESP) being less than a specific value is generally greater than the others. The simulation shows the mainstream scheme's inferiority from the perspective of multiple pollutant control.

The discrepancy in cumulative probability distribution of the NPV of the technology schemes varies from 0 to 330 million U.S. dollars. In the range of 93–200 million U.S. dollars, the discrepancy between the mainstream scheme and the other schemes is greater than in other ranges, meaning that NPV gain from substituting the mainstream scheme with alternative schemes has greater probability in this range.

The order of magnitudes of technology scheme substitution for a standard coal-fired power plant is million U.S. dollars. According to investment cost and newly increased installed capacity in coal-fired power sector in 2013 (National Bureau of Statistics of China, 2015a,b), investment cost per capacity is about 375 U.S. $/kW in this sector. Therefore, investment cost for constructing a standard power plant with install capacity of 600 MW is 225 million U.S $ in 2013. Difference of a couple of million dollars coming from the application of different air pollution control technology scheme, is equivalent to 0.5–4.5% of the investment cost of a plant. It could be important for an individual plant. This disparity will be further enlarged and significant from a perspective of sector. This value (million U.S. dollars) may decrease if a lower intake fraction is applied to the estimation when the standard plant is changed to other locations that affect fewer people. However, given that the installed capacity of coal-fired power plants was as large as 0.75 million MW in 2013 and covered a large population base in many provinces, the NPV gain from technology scheme substitution can be significant if it is implemented nationwide.

We are not attempting to make suggestions about technology schemes in this paper. Our focus is to reveal the possible risk of economic efficiency loss from a process of technology innovation, diffusion and deployment without policies that specifically address the complexity of air pollution. Currently, a single technology (or technology schemes) dominates the air pollution technology market, which is the outcome of a process of technology diffusion that has been ongoing since the early 1990s, when air pollution control began to enter government policy. It is a predictable outcome from the perspective of market mechanisms. However, it is not the best outcome in terms of the health risks from air pollution.

Quick economic development and rapid changes in China's industrial sector have caused uncertainty and complexity around air pollution and climate change. This complexity is mainly due to the multiple highly concentrated pollutants that simultaneously exist and react in the atmosphere. The uncertainty arises from the quickly changing composition of multiple primary pollutants over time, and the varying composition of multiple primary pollutants across the nation. Additionally, human perception of air pollution and climate change always lags behind the real problem. Complexity and uncertainty pose challenges for technology deployment to solve future air pollution and climate change issues.

Our analysis shows that the dominant technology scheme in China's coal-fired power sector suffers efficiency losses in curbing the health effects of multiple pollutants. Alternative schemes with better economic efficiency exist, if the synergistic effects of the technologies are taken into account. To respond to future challenges posed by complexity, technology policies should note the synergistic effects of some technologies for a more holistic pollutant control framework. Technology policies should also cultivate diverse technologies and facilitate their diffusion to reduce the risk of forming a dominant technology with lower efficiency.

3.3. NPV for substitute technology schemes at the provincial level

3.3.1. Scenario analysis of technology scheme substitution

In Section 3.3, we predict the NPV gain of technology scheme substitution for provinces, based on scenario setting. We set 2013 as the base year, and 2020 as the target year. At the provincial level, the installed capacity of each province in 2020 is linearly predicted based on the 2014 national desulfurization and denitration facility inventory (MEP of China, 2014), assuming a 36% increase by 2020, based on the 2013 level (see supplementary Table S.4). In 2020, three scenarios are assumed to represent different usage proportions of technology schemes. The business-as-usual (BAU) scenario in 2020 represents the same proportion of technology schemes as in 2013. According to the *Notice on plan of energy conservation and emission reduction in the 13th Five-Year Plan* (The State Council, 2017), all existing units are required to install denitration facilities after 2013. The *Action plan on upgrading and transforming energy conservation and pollutant emission reduction in the coal-fired power sector (2014–2020)* (National Development and Reform Commission, 2014) requires stricter air pollutant emission concentration limits than in the past. It also regulates transforming to ultra-low pollutant emission for coal-fired power plants. As such, a total emission cap (TEC) scenario and an upgrading-and-transforming (UAT) scenario assume that the application proportions of SCR in the sector

are 86% and 100%, respectively. The application proportions of ESP to FFs are set as 65%:35% in the TEC scenario and 50%:50% in the UAT scenario, using a study (Wang et al., 2014) as a reference. The total application proportions of wet FGD, CFB and SD are assumed to be 85% in all scenarios, and their relative proportions are assumed to be 78%:3%:5% in the TEC scenario and 73%:6%:7% in the UAT scenario. The application percentage of the technology schemes (combinations of desulfurization technology, denitration technology, and PM control technology) are estimated based on the above scenario assumptions and shown in supplementary Table S.5.

To run the estimation at the provincial level, the intake fraction is adjusted to better suit the national situation. The above mentioned intake fractions (Zhou et al., 2006) are used as a reference, as intake fractions were estimated for 29 plants located in 29 provinces. In Section 3.3, the intake fraction of $PM_{2.5}$ is replaced by PM_3 due to data availability. Due to the similar particle sizes of $PM_{2.5}$ and PM_3, the estimations at the plant level and nation and provincial levels are basically constant. In this study, we use an average of these 29 intake fractions to run the estimation at the national level first, and then use the 29 individual intake fractions to run the estimation at the provincial level (excluding Tibet, Taiwan, Hong Kong, and Macau). Due to there being no data available for Xinjiang and Heilongjiang provinces, the intake fractions of Qinghai and Jilin are used.

3.3.2. Provincial NPV of technology substitution

The estimation at the national level (see Fig. 2) shows that the base value of the BAU scenario is 37.6 billion U.S. dollars. This is about 2% of the 2013 total national investment in environmental protection. As the estimates of health benefits in this study are not a full measure of the benefits, the results may underestimate the magnitude of the NPV. In the BAU scenario, the probability of the NPV being greater than 37.6 billion U.S. dollars is 43.07%. The UAT scenario has the highest numbers of avoided death and chronic bronchitis, and also the highest cost. The probabilities of the NPV being greater in the TEC and UAT scenarios than its base value in the BAU scenario are 61.32% and 65.69%, respectively.

The NPV of provinces in 2013 and in the three scenarios in 2020 (see Fig. 3) show that higher NPV regions are located in provinces with greater coal-fired power plant installed capacities and larger populations, such as Jiangsu, Hebei, Inner Mongolia, Shandong, Henan, and Guangdong. This result is similar to other study (Xie et al., 2016). In China, the provinces with the largest coal-fired power plant installed capacities basically cover the provinces with the largest populations. In terms of provincial population scale in 2014 (National Bureau of Statistics of China, 2015a,b), the top ten provinces with largest population are Guangdong, Shandong, Henan, Sichuan, Jiangsu, Hebei, Hunan, Anhui, Hubei, Zhejiang, accounting for about 58% of the national population. According to provincial installed capacity of coal-fired power sector in 2014 (National Bureau of Statistics of China, 2015a,b), these ten provinces occupy about 51% of the national installed capacity of coal-fired power sector. This implies that the cost and health benefits of technology substitution can highly spatially coincide, which can lead to economic efficiency improvement via the technology policy improvements proposed in this paper.

For those provinces that have high populations and high installed capacities of coal-fired power plants, the health effects of air pollution and its long-term effect on local economic development should marked as important. These provinces have a high impetus for economic growth, and sometimes focus less on the health risks of labor. However, labor productivity and supply could be significantly affected by air pollution, which could undermine the long-term sustainability of economic growth. Thus, technology policies regarding air pollution should be linked with public health objectives.

3.4. NPV estimation sensitivity

To better understand the simulation results, a one-way sensitivity analysis was conducted to identify the key factors driving changes in the NPV of the technology schemes. Holding other variables constant, the sensitivity of the effect of one variable on the NPV estimation was analyzed using the Monte-Carlo simulation method. The amplitudes of the NPV prediction for each variable were ranked according to width. For the mainstream scheme, the sensitivity analysis results showed that the eight parameters driving NPV most strongly are: intake fraction of secondary nitrate forming from NOx emissions, VSL, marginal health risks of mercury emission, emission factor of NOx from uncontrolled plant, C-R coefficient of chronic mortality, all-cause mortality, ratio of value of a statistical case of chronic bronchitis to a statistical life, and C-R coefficient of chronic bronchitis. Although the most sensitive parameter rankings are not identical for all seven technology schemes, the intake fractions of secondary nitrate forming from NOx emission and VSL are always the two most sensitive. The main reason for this is that

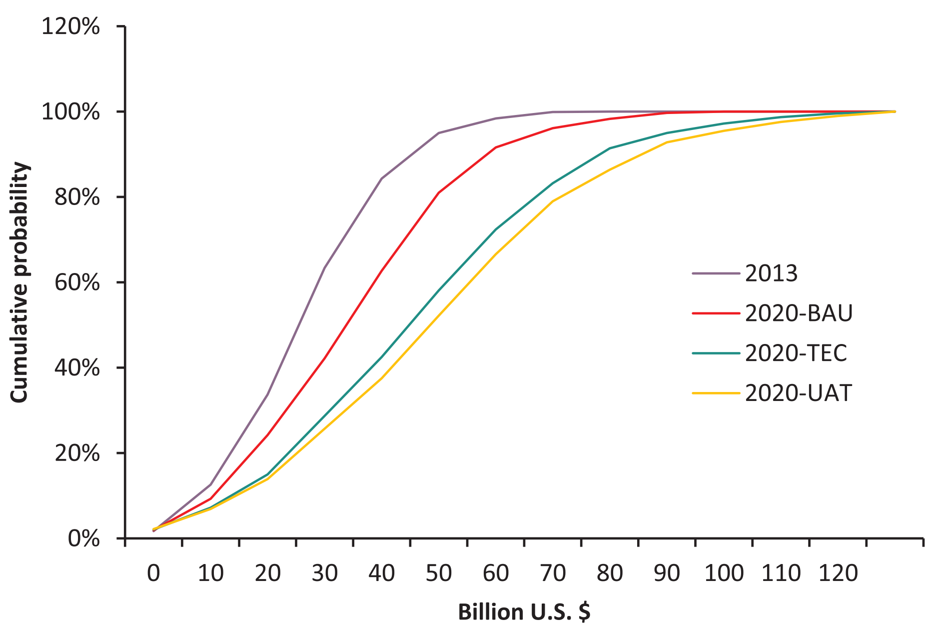

Fig. 2. Cumulative probability distribution of NPV in three scenarios.

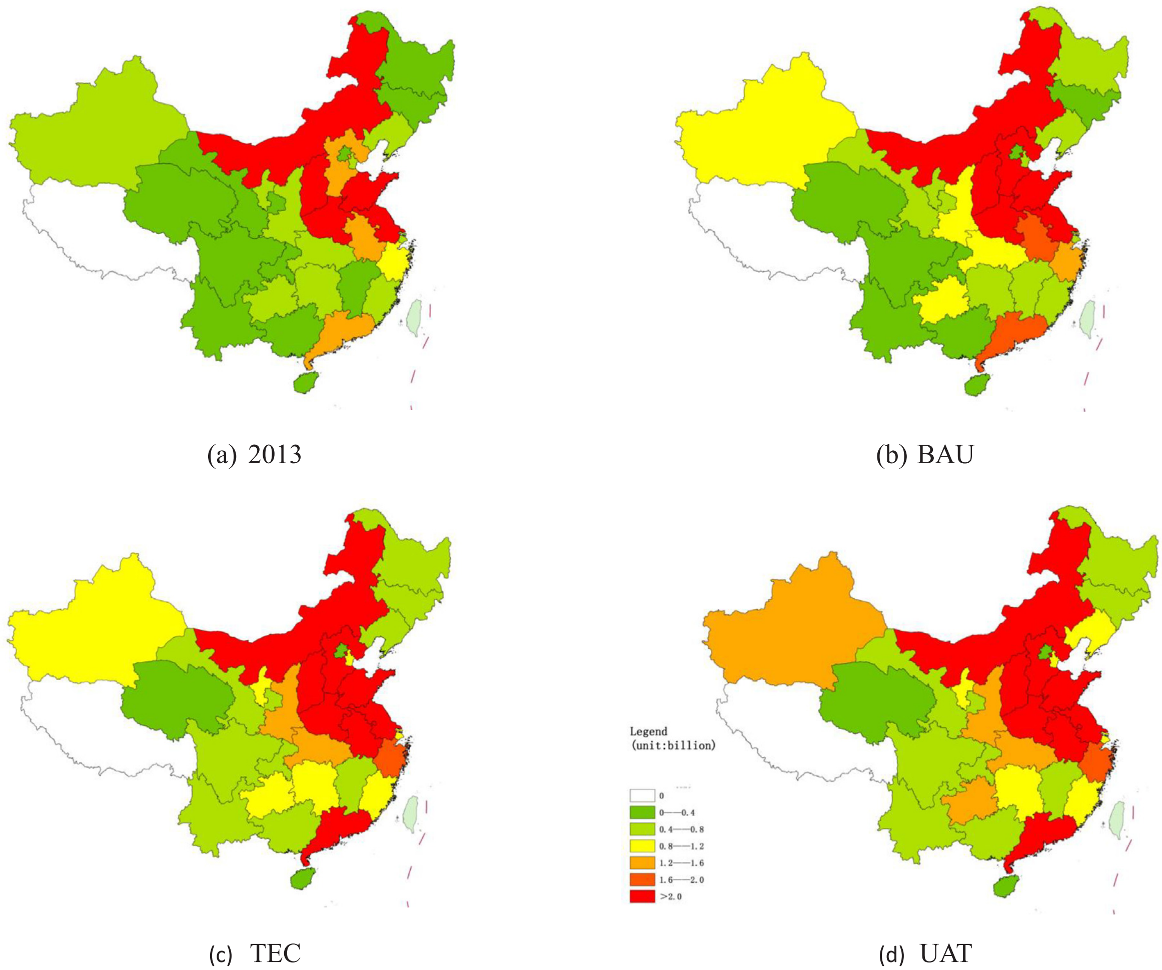

Fig. 3. NPV of provinces in the 2013 and 2020 scenarios.

health damage attributed to NOx emission is comparatively greater. The sensitive parameters were calculated by a one-way sensitivity analysis, which holds other parameters constant when conducting the prediction. If correlations between parameters are taken into account, the results may be different.

3.5. Uncertainties of the results

The NPV estimation in this study use Monte-Carlo simulation to address the issue of uncertainties. In the simulation, the uncertainties of incremental cost of technology schemes, pollutant emission to impact on health endpoint, and VSL are simply expressed by the assumption of the evenly distribution of technology cost, iF, concentration-response coefficients, risks of all-cause death and chronic bronchitis, and VSL. However, the real distribution of these parameters may not be consistent with the assumptions. Changing the distribution in the assumption could lead to different results. Thus, the uncertainties are not entirely reflected in this analysis.

In addition, the assumption of standard plant does not consider the variation of the characteristics of the plants, such as install capacity. If the variation were considered in the simulation, the results could be changed. Similarly, our simulation does not consider technology change over time. The economic efficiency of the involved technology schemes may also change if cost reduction induced by technology change were considered.

4. Conclusions

The broad spectrum of environmental protection technologies and their health effects raise concerns about path dependency and the “lock-in” effect of environmental protection technologies. This study focuses on China’s coal-fired power plants and compares the NPVs of their air pollution control technologies, due to the challenges posed to technology deployment for multiple-pollutant emission control in this sector. We explored whether there is potential for improving the economic efficiency of technology deployment in this sector, and shed light on the direction for improvement of current technology policy.

In terms of analyzing desulfurization, denitration and de-dusting facilities, there is a dominant technology scheme of air pollution control. A Monte-Carlo simulation based cost-benefit analysis was conducted to evaluate and compare the efficiency of the mainstream scheme and alternative schemes. The results indicate that there are alternative schemes with better NPV than the current mainstream scheme employed in China, meaning that there is long-term economic efficiency loss through the current mainstream scheme. We estimated the NPV of implementing various technology schemes at the national and provincial level, in addition to plant-level analysis. The order of magnitudes of technology scheme substitution for a standard coal-fired power plant is million U.S. dollars. Given that the installed capacity of coal-fired power plants was as large as about 0.75 million MW in 2013 and covered a large population base across many provinces, the NPV is significant at the national level. Provinces with larger installed capacities of their coal-fired power plants and higher populations, such as Jiangsu, Shandong, and Guangdong, will gain a higher positive NPV by

substituting the mainstream scheme with alternative schemes.

Our analysis suggests that single-technology dominated schemes can risk long-term economic efficiency loss, due to the complexity of air pollution not being fully understood by humans. The underlying implications of the results are as follows. First, technology policies should note the synergistic effects of technologies and combine them into a more holistic pollutant control framework. Second, research and development should be encouraged for diverse technologies, and technology policies that better facilitate diverse technology diffusion in the real market should be created. Third, public health objectives should be considered when improving related technology policies. Fourth, the economic analysis, especially the cost-benefit analysis together with NPV comparison, can provide valuable support for policy making to address the economic efficiency of policy design.

Acknowledgements

This work was funded by the National Natural Science Foundation of China (71503279), and Special Fund of State Key Joint Laboratory of Environment Simulation and Pollution Control (17K01ESPCP). Thanks are also given to Miss Ling Zhang for her assistant.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2019.02.039.

References

Apte, J.S., Marshall, J.D., Cohen, A.J., Brauer, M., 2015. Addressing global mortality from ambient PM2. 5. Environ. Sci. Technol. 49 (13), 8057–8066.
Arthur, W.B., 1989. Competing technologies, increasing returns, and lock-in by historical events. Econ. J. 99 (394), 116–131.
Axelrad, D.A., Bellinger, D.C., Ryan, L.M., Woodruff, T.J., 2007. Dose-response relationship of prenatal mercury exposure and IQ: an integrative analysis of epidemiologic data. Environ. Health Perspect. 115 (4), 609.
Balmes, J.R., Fine, J.M., Sheppard, D., 1987. Symptomatic bronchoconstriction after short-term inhalation of sulfur dioxide. Am. Rev. Respir. Dis. 136, 1117–1121.
Brook, R.D., Rajagopalan, S., Pope, C.A., Brook, J.R., Bhatnagar, A., Diez-Roux, A.V., Holguin, F., Hong, Y., Luepker, R.V., Mittleman, M.A., et al., 2010. Particulate matter air pollution and cardiovascular disease. Circulation 121 (21), 2331–2378.
Burnett, R.T., Pope III, C.A., Ezzati, M., Olives, C., Lim, S.S., Mehta, S., Shin, H.H., Singh, G., Hubbell, B., Brauer, M., et al., 2014. An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. Environ. Health Perspect. 122 (4), 397.
Cao, J., Yang, C., Li, J., Chen, R., Chen, B., Gu, D., Kan, H., 2011. Association between long-term exposure to outdoor air pollution and mortality in China: a cohort study. J. Hazard. Mater. 186 (2), 1594–1600.
Chen, X., Zhang, L., Huang, J., Song, F., Zhang, L., Qian, Z., Trevathan, E., Mao, H., Han, B., Vaughn, M., et al., 2016. Long-term exposure to urban air pollution and lung cancer mortality: a 12-year cohort study in Northern China. Sci. Total Environ. 571, 855–861.
Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proc. Natl. Acad. Sci. 110 (32), 12936–12941.
China Electricity Council, 2010. Electric power industry statistics assembly.
Cohen, J.T., Bellinger, D.C., Shaywitz, B.A., 2005. A quantitative analysis of prenatal methyl mercury exposure and cognitive development. Am. J. Prev. Med. 29 (4), 353.
Cropper, M., Gamkhar, S., Malik, K., Limonov, A., Partridge, I., 2012. The health effects of coal electricity generation in India (June 26, 2012). Resources for the Future Discussion Paper No. 12–25.
Crump, K.S., Kjellstr, T., Shipp, A.M., Silvers, A., Stewart, A., 1998. Influence of prenatal mercury exposure upon scholastic and psychological test performance: benchmark analysis of a New Zealand cohort. Risk Anal. 18 (6), 701–713.
David, P.A., 1985. Clio and the economics of QWERTY. Am. Econ. Rev. 75 (2), 332–337.
Dockery, D.W., Pope, C.A., Xu, X., Spengler, J.D., Ware, J.H., Fay, M.E., Ferris Jr, B.G., Speizer, F.E., 1993. An association between air pollution and mortality in six US cities. N. Engl. J. Med. 329 (24), 1753–1759.
Dominici, F.J., Samet, M., Zeger, S.L., 2000. Combining evidence on air pollution and daily mortality from the 20 largest US cities: a hierarchical modelling strategy. J. Roy. Statist. Soc.: Series A (Statist. Soc.) 163 (3), 263–302.
Endcoal, 2017. Plant Combustion Technology-July 2017. https://endcoal.org/wp-content/uploads/2017/07/PDFs-for-GCPT-July-2017-Combustion.pdf (Accessed on Oct. 5, 2018).
Erickson, P., Kartha, S., Lazarus, M., Tempest, K., 2015. Assessing carbon lock-in. Environ. Res. Lett. 10 (8), 84023.
Feng, L., Liao, W., 2016. Legislation, plans, and policies for prevention and control of air pollution in China: achievements, challenges, and improvements. J. Cleaner Prod. 112, 1549–1558.
Ghio, A.J., Huang, Y.T., 2004. Exposure to concentrated ambient particles (CAPs): a review. Inhalation Toxicol. 16 (1), 53–59.
Goldberg, M.S., Burnett, R.T., Bailar, J.C., Brook, J., Bonvalot, Y., Tamblyn, R., Singh, R., Valois, M., 2001. The association between daily mortality and ambient air particle pollution in Montreal, Quebec: nonaccidental mortality. Environ. Res. 86 (1), 12–25.
Hammitt, J.K., Zhou, Y., 2006. The economic value of air-pollution-related health risks in China: a contingent valuation study. Environ. Resour. Econ. 33 (3), 399–423.
Ho, M.S., Wang, Z., 2014. Green growth (for China): A literature review (August 15, 2014). Resources for the Future Discussion Paper No. 14-22.
Huang, D.H., Andersson, Zhang, S., 2015. Willingness to Pay to Reduce Health Risks Related to Air Quality: Evidence from a Choice Experiment Survey in Beijing (mimeo). Peking University, Toulouse School of Economics.
Jin, Y.H., Andersson, Zhang., S., 2017. China's cap on coal and the efficiency of local interventions: a benefit-cost analysis of phasing out coal in power plants and in households in Beijing. J. Benefit-Cost Anal. 8, 1–40.
Kagawa, J., 1984. Evaluation of biological significance of nitrogen oxides exposure. Tokai J. Exp. Clin. Med. 10 (4), 349–353.
Katsouyanni, K., Touloumi, G., Samoli, E., Gryparis, A., Le Tertre, A., Monopolis, Y., Rossi, G., Zmirou, D., Ballester, F., Boumghar, A., et al., 2001. Confounding and effect modification in the short-term effects of ambient particles on total mortality: results from 29 European cities within the APHEA2 project. Epidemiology 12 (5), 521–531.
Kline, D., 2001. Positive feedback, lock-in, and environmental policy. Policy Sci. 34 (1), 95–107.
Levy, J.I., Baxter, L.K., Schwartz, J., 2009. Uncertainty and variability in health-related damages from coal-fired power plants in the United States. Risk Anal. 29 (7), 1000–1014.
Liebowitz, S.J., Margolis, S.E., 1995. Path dependence, lock-in, and history. J. Econ. Organ. 11, 205.
Liu, J., 2014. Utilizing Coal in a Clean Way is the Road for Scientifically Combating Haze Pollution in the Current Stage.
Mattauch, L., Creutzig, F., Edenhofer, O., 2015. Avoiding carbon lock-in: policy options for advancing structural change. Econ. Model. 50, 49–63.
MEP of China, 2014. Announcement on National Desulfurization and Denitration Facility Inventory.
National Bureau of Statistic of China, 2015. China Statistical Yearbook.
National Bureau of Statistics of China, 2016. China Electric Power Yearbook.
National Bureau of Statistics of China, 2015. China Electric Power Yearbook.
National Development and Reform Commission, 2014. Action plan on upgrading and transforming energy conservation and pollutant emission reduction in coal-fired power sector (2014-2020). http://www.zhb.gov.cn/gkml/hbb/gwy/201409/t20140925_289556.htm (Accessed on Oct. 19, 2017).
Pope III, C.A., Burnett, R.T., Turner, M.C., Cohen, A., Krewski, D., Jerrett, M., Gapstur, S.M., Thun, M.J., 2011. Lung cancer and cardiovascular disease mortality associated with ambient air pollution and cigarette smoke: shape of the exposure-response relationships. Environ. Health Perspect. 119 (11), 1616.
Pope III, C.A., Burnett, R.T., Thun, M.J., Calle, E.E., Krewski, D., Ito, K., Thurston, G.D., 2002. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA 287 (9), 1132–1141.
Pope, C.A., Turner, M.C., Burnett, R., Jerrett, M., Gapstur, S.M., Diver, W.R., Krewski, D., Brook, R.D., 2014. Relationships between fine particulate air pollution, cardiometabolic disorders and cardiovascular mortality. Circ. Res. 114.
Pope, C.A., Thun, M.J., Namboodiri, M.M., Dockery, D.W., Evans, J.S., Speizer, F.E., Heath, C.W., et al., 1995. Particulate air pollution as a predictor of mortality in a prospective study of US adults. Am. J. Respir. Crit. Care Med. 151 (3), 669–674.
Qi, Y., Stern, N., Wu, T., Lu, J., Green, F., 2016. China's post-coal growth. Nat. Geosci. 9 (8), 564–566.
Rice, G.J., Hammitt, K., Amar, P.K., 2005. Economic valuation of human health benefits of controlling mercury emissions from US coal-fired power plants. In: USA: NESCAUM, Northeast States for Coordinated Air Use Management, pp. 223.
Ruckerl, R., Schneider, A., Breitner, S., Cyrys, J., Peters, A., 2011. Health effects of particulate air pollution: a review of epidemiological evidence. Inhal. Toxicol. 23 (10), 555–592.
Salonen, J.T., Sepp, K., Nen, A., Nyyss, K., Nen, O., Korpela, H., Kauhanen, J., Kantola, M., Tuomilehto, J., Esterbauer, H., Tatzber, F., Salonen, R., 1995. Intake of mercury from fish, lipid peroxidation, and the risk of myocardial infarction and coronary, cardiovascular, and any death in eastern Finnish men. Circulation 91 (3), 645–655.
Samet, J.M., Dominici, F., Curriero, F.C., Coursac, I., Zeger, S.L., 2000. Fine particulate air pollution and mortality in 20 US cities, 1987–1994. N. Engl. J. Med. 343 (24), 1742–1749.
Shih, Y., Tseng, C., 2015. Co-benefits of mercury reduction in Taiwan: a case study of clean energy development. Sustain. Sci. 10 (1), 61–73.
Song, C., Wu, L., Xie, Y., He, J., Chen, X., Wang, T., Lin, Y., Jin, T., Wang, A., Liu, Y., et al., 2017. Air pollution in China: status and spatiotemporal variations. Environ. Pollut. 227, 334–347.
Spadaro, J.V., Rabl, A., 2008. Global health impacts and costs due to mercury emissions. Risk Anal. 28 (3), 603–613.
Sundseth, K., Pacyna, J.M., Pacyna, E.G., Munthe, J., Belhaj, M., Astrom, S., 2010. Economic benefits from decreased mercury emissions: projections for 2020. J. Cleaner Prod. 18 (4), 386–394.
The State Council, 2014. Action Plan on Upgrading and Transforming Energy Conservation and Pollutants Emission Reduction in Coal-fired Power Sector (2014-2020). http://www.gov.cn/gongbao/content/2015/content_2818468.htm (Accessed on Oct. 1st, 2018) (in Chinese).
The State Council, 2017. Notice on plan of energy conservation and emission reduction in

the 13th Five-Year Plan. http://www.gov.cn/zhengce/content/2017-01/05/content_5156789.htm (Accessed on Oct. 19, 2017).
U.S. EPA, 2011. Benefits and costs of the clean air act 1990-2020, the second prospective study.
UNEP, 2013. Global Mercury Assessment 2013: Sources, Emissions, Releases and Environmental Transport. UNEP Chemicals Branch, Geneva, Switzerland.
Unruh, G.C., 2000. Understanding carbon lock-in. Energy Policy 28 (12), 817–830.
Unruh, G.C., 2002. Escaping carbon lock-in. Energy Policy 30 (4), 317–325.
Virtanen, J.K., Voutilainen, S., Rissanen, T.H., Mursu, J., Tuomainen, T., Korhonen, M.J., Valkonen, V., Sepp, K., Nen, A., Laukkanen, J.A., Salonen, J.T., 2005. Mercury, fish oils, and risk of acute coronary events and cardiovascular disease, coronary heart disease, and all-cause mortality in men in eastern Finland. Arterioscler. Thromb. Vasc. Biol. 25 (1), 228–233.
Wang, J., Wang, Z., Zhao, B., Wang, S., Hao, J., 2014. Cost-effectiveness analysis of multi-pollutant emission reduction in power sector of China. Res. Environ. Sci. 27 (1), 1314–1322 in Chinese.
Wang, S., Hao, J., Ho, M.S., Li, J., Lu, Y., 2006. Intake fractions of industrial air pollutants in China: estimation and application. Sci. Total Environ. 354 (2), 127–141.
World Bank, 2007. Cost of Pollution in China: Economic Estimates of Physical Damages. World bank, Washington D C.
World Health Organization, 2010. WHO Air Quality Guidelines for Particulate Matter, Ozone, Nitrogen Dioxide and Sulfur Dioxide: Summary of Risk Assessment. World Health Organization, Copenhagen.
Xie, Y., Dai, H., Dong, H., Hanaoka, T., Masui, T., 2016. Economic impacts from PM2.5 pollution-related health effects in China: a provincial-level analysis. Environ. Sci. Technol. 50 (9), 4836–4843.
Zhou, Y., Levy, J.I., Hammitt, J.K., Evans, J.S., 2003. Estimating population exposure to power plant emissions using CALPUFF: a case study in Beijing, China. Atmos. Environ. 37 (6), 815–826.
Zhou, Y., Levy, J.I., Evans, J.S., Hammitt, J.K., 2006. The influence of geographic location on population exposure to emissions from power plants throughout China. Environ. Int. 32 (3), 365–373.